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Recognizing and Modeling Influence in Social Media Language

Yang Liu
UNIVERSITY OF TEXAS AT DALLAS
800 W CAMPBELL RD
RICHARDSON, TX 75080

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Final Report

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14. ABSTRACT Social influence has a profound impact on people's emotion, opinion, and behavior. Prior work has exploited different information, from network analysis and the content. This project aims to focus on the language aspect in addition to social interaction to study influence. We have investigated the following problems in this reporting period: - predict review helpfulness. The review usefulness used in previous work has not been systematically tested. Second, whether a user rates a review as helpful depends on not only the review content but also the context in which it was written, such as whether the user agrees with the reviewer's opinion. Merely using features taken from the review limits a system's predictive power. Our work so far has focused on identifying these key research issues in existing work. - extract implicit aspects in reviews. So far we have found some characteristics of implicit aspects (they are common, overlap with explicit aspects, functionality of opinions, attached to specific attributes) and just started data collection effort.					
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Recognizing and Modeling Influence in Social Media Language

PI: Yang Liu

The University of Texas at Dallas

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Final report

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Social influence has a profound impact on people's emotion, opinion, and behavior. This project aims to focus on the language aspect in addition to social interaction to study influence and related aspects in social media language. In particular, in the past year our objective is advancing performance for predicting review helpfulness and extracting implicit aspects in social media text.

1) Review Helpfulness Prediction

Product reviews written by users in online stores, such as Amazon.com, have become a key resource for consumers looking to make well-informed decisions. Given that the quality of these reviews can vary greatly and that products frequently have too many reviews for a single customer to read, there is an increasing need for systems that can automatically determine the quality of product reviews. Researchers have used user votes such as those elicited by Amazon's "Did you find this review helpful?" (Yes/No) prompt, as indicators of the "helpfulness" of a review. The ratio of "helpful" votes a review receives has been taken as a measure of its helpfulness. The goal of helpfulness prediction is to build systems that predict this ratio. Results: We noticed that existing work on helpfulness prediction has several key weaknesses, which we attempt to address. First, existing work has focused on finding useful features from a given review for helpfulness prediction, but their usefulness have not been systematically tested. Second, whether a user rates a review as helpful or not depends on not only the review content but also the context in which it was written, such as whether the user agrees with the reviewer's opinion. Merely using features taken from the review limits a system's predictive power. Finally, systems were evaluated on different datasets, making it hard to determine the state of the art. Our work so far has focused on identifying these key research issues. Our results are available in the following publication:

Modeling and Prediction of Online Product Review Helpfulness. Gerardo Ocampo Diaz and Vincent Ng. Proceedings of the 56th Annual Meeting of the ACL (Vol. 1: Long Papers), 2018.

2) Implicit Aspect Extraction

User reviews in online stores and review websites are gold mines of information for manufacturers, retailers, and consumers. Reviewers' opinions are embedded in text reviews, but the large number of reviews posted every day makes it infeasible to manually process them. The goal of aspect extraction is to automatically identify opinions expressed on different aspects of a product. The two main types of aspect extraction are: a) explicit aspect extraction, which attempts to recover expressed opinions on explicit aspects of a product; and b) implicit aspect extraction, which attempts to recover opinions expressed implicitly. Most work has focused on explicit aspect extraction. Implicit aspect extraction is arguably harder and much-less studied.

Worse still, there is no consensus on how implicit aspect extraction should be performed and evaluated.

Since there are no public datasets for implicit aspect extraction, we attempt to build the first such dataset, which should allow us to a) encourage researchers to pursue implicit aspect extraction, and b) define what implicit aspect extraction should consist of and how it should be evaluated.

Results: We do not have publishable results yet, but our research so far has yielded the following findings. First, implicit aspects are quite common in reviews: they are at least as frequent as explicit aspects. Second, implicit and explicit aspects do overlap, i.e., aspects that are mentioned explicitly are sometimes present implicitly. Third, a lot of the difficulties found when performing implicit aspect extraction seem to stem from the fact that aspect based sentiment analysis makes the assumption that opinions are always expressed in terms of concrete aspects of a product, where in reality, opinions are many times expressed in terms of functionality, i.e., product behavior. Finally, inferring specific attributes is sometimes not enough. e.g., inferring resolution from "Images are very detailed" is not enough, extra steps must be taken to infer the specific component on which opinions are expressed (in this case, "screen"). This has also led us to reconsider the definition of "aspect".